Edge on Wheels in 6G with Omnibus Networking

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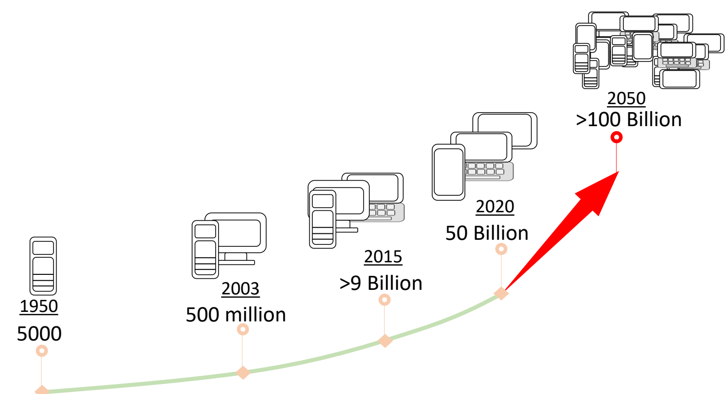
***Abstract*—In recent years, both the scientific community and industry are focusing on moving computational resources from the centralized Cloud, with remote datacenters, to decentralized computing, closer to the source or the so called "edge" of the network. This is in light of the fact that the Cloud system alone cannot support network demands of a growing number of time-critical new applications, such as self-driving vehicles, augmented reality (AR)/ virtual reality (VR) techniques, advanced robotics, and smart city & energy systems. While decentralized edge computing will form the backbone of future heterogeneous networks, it is still in its infancy and there is no comprehensive platform to date. In this article, we propose an edge architecture, OMNIBUS solution, which enables continuous distribution of computational capacity for end-devices in different localities by exploiting moving cars, as storage and computation resources. Scalability and adaptability differentiates the proposed project from existing edge computing models. In contrast to these models, the proposed project has the potential to scale infinitely and increase the speed of the networks. As a proof-of-concept, we provide a reference architecture and implementation of the project, which rests on developing two predictive models: (i) to learn timing and direction of vehicular movements, as to ascertain computational capacity for a given locale and (ii) to introduce a theoretical framework for sequential to parallel conversion in learning, optimization and caching under contingent circumstances, due to vehicles being in motion.**

I. Introduction

In 2015, there were more than an estimated nine billion connected devices around the world including smart phones and computers [1]; Cisco predicts that by 2020 50 billion "things" will be connected to the Internet (Fig. 1) [2]. The centralized cloud system alone will be insufficient to handle the future networks efficiently, wherein is an environment of trillions of devices equipped with sensors, geared to collect huge amounts of data, drawing inferences to carry out an action. To move massive amounts of data, in connected devices to the Cloud to be analyzed, creates very crowded traffic on the network infrastructure [3, 4] . Moreover, the transfer of data back and forth between the Cloud and individual devices increases latency while many new applications, such as self-driving vehicles, remote surgery, AR/VR, 8K video, advanced robotics in manufacturing, and drone surveillance communication, require real-time, ultra-low delay performance [5, 3].

In view of these challenges, data center operations are being pushed to the "edge" of the network. The edge allows for certain time-critical and security-sensitive Artificial Intelligence (AI) applications to operate either entirely on a device, or in conjunction with localized datacenters. None of the proposed edge architectures [6, 7, 8, 9], so far, are sufficient to handle the data heavy future of the networks. Most of the proposed solutions focus on installing edge devices to singular locations (e.g. factories, shopping malls) or around specific geographic areas (urban centers), which bear the cost of additional infrastructure deployments [10, 11, 12, 13]. There is also a growing body of research on exploiting connectivity among end-devices, in close proximity to process tasks cooperatively in local area computation groups, though these efforts are again limited in scope.

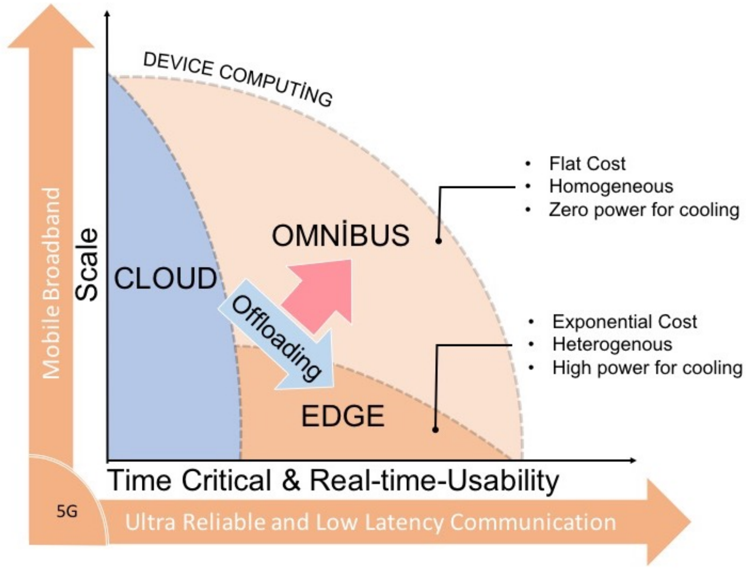
Fig. 1. A Number of Connected Devices



The main contribution of this article is to develop an OMNIBUS approach to advance a decentralized computing and storage architecture using vehicles. Road vehicles emerge as the most promising candidate for future distributed datacenters on the edge of the network for two primary reasons: (1) Most road vehicles display predictable movement patterns (2) hardware capabilities for storage and computing in cars are expected to advance tremendously in the coming years. In our architecture, clusters of cars form a powerful local hub in individual areas capable of offering high computational virtualized resources for end-devices.

In building our platform, we will address two interrelated scientific challenges: First, the creation of a mobility prediction model to determine the flow of individual cars in a given area at a certain time. With this, a local hub can be created for end-devices in that area by using cars as building blocks. Efficient algorithms can be developed to ensure computing and storage workloads for individual areas, as cars move in and out of a given area. Second, in order to minimize networking overheads as cars move in and out of a region, it is necessary to study required distribution of computing and storage resources among cars. The main scientific contribution of the OMNIBUS approach will be to initiate a theoretical framework for sequential to parallel conversion in learning, optimization, and caching algorithms under unreliable circumstances for time-critical performance.

Fig. 2. Our vision for the future of edge computing: Scalable, ultra-low latency networking for the time critical applications at a flat cost and energy efficient.



II. Edge Computing

The Cloud has been an important solution for companies looking to scale their computational operations without investing in new infrastructure and to cut down on operational costs by transferring their datacenters to cloud providers. While the Cloud catalyzed growth and adoption of big data, it hide the costs and limitations related to network latency, security, and privacy. As a result, in recent years, discussion on computational operations increasingly moved from the centralized Cloud, with remote datacenters, to decentralized computing, closer to the source or the so called "edge" of the network.

Edge solutions allow information processing to take place at the device or gateway level. This reduces the need to transfer data back and forth between the cloud or a data center, therefore, decreasing latency, bandwidth requirements, and connectivity dependencies. Outside of technical reasons, decentralized computing is energy saving given the power and cooling costs associated with big datacenters. As importantly, research on edge computing is driven by security and privacy concerns related to the centralized Cloud on the part of states, firms and consumers. At the same time, falling prices in compute and storage, together with the rise of machine learning, is driving the adoption of edge computing. According to IDC, by 2019, a minimum of 40 % of the data created by IoT "will be stored, processed, analyzed, and acted upon close to, or at the edge of the network" [14].

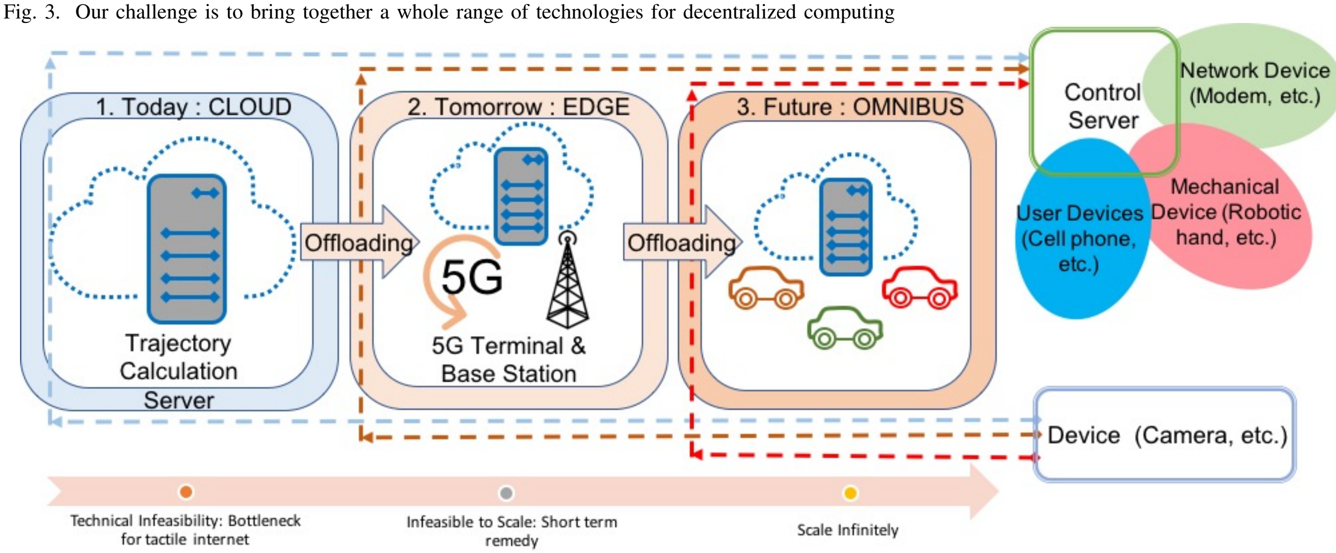
Systems typically known as edge computing include Cyber Foraging [15, 16], Cloudlets [17], Fog Computing, and mobile edge computing (recently, the name replaced by Multi-Access Edge Computing). Multi-Access Edge Computing was initiated by the European Telecommunication Standards Institute (ETSI) in 2014 with a focus on mobile networks and Virtual Machine technology [18]. In 2017, its scope was expanded to incorporate non-mobile network requirements, and other virtualization technologies. The concept initially envisioned providing cloud-computing capabilities at the edge of mobile networks, and within the Radio Access Network (RAN), by deploying mobile edge computing servers at LTE macro base stations (eNodeB) sites, 3G Radio Network Controller (RNC) sites, and at multi-Radio Access Technology (RAT) sites. The ETSI initiative has also been assigned a key role to standardize the Application Programming Interfaces (APIs) between the mobile edge platform and the applications, with an aim to foster innovation in an open environment.

Fog computing, a concept introduced by Cisco in 2012, is an extension of the cloud computing paradigm, from the core to the edge of the network [19]. Hence, unlike Mobile-Edge computing (MEC), fog is strongly linked to the cloud, unable to operate in a standalone mode. As a result, there has been a special focus on communication between the fog and the cloud [20, 21, 22]. Moreover, unlike MEC, which is generally deployed at a base station, fog nodes can be placed anywhere with a network connection, e.g. factory floor, top of a power pole, a railway track, a vehicle, etc. [19], Cisco offers application platforms to simplify fog application development and Cisco Fog Data Services for data analytics [23].

In parallel, big Internet companies are rolling out edge infrastructure: Facebook is building micro datacenters for certain types of applications and workloads. Amazon has launched Amazon Web Services (AWS) Greengrass, allowing for developers to move some tasks to the device itself. There are also companies that describe themselves as edge companies, including EdgeConneX and vXchnge, that are building networks of urban datacenters. For instance, a startup, Vapor IO developed micro-centers, which can be deployed anywhere.

Most of the proposed applications bear the cost of additional infrastructure deployment, whether it is installing edge devices to singular locations (e.g. factories, shopping malls) or around specific geographic areas (urban centers). Furthermore, scalability is affected as more and more people perform transactions within a given specific edge domain. In contrast, with the

Fig. 3. Our challenge is to bring together a whole range of technologies for decentralized computing



platform we propose, scalability rises with adoption. In other words, as more and more users require computing and storage transactions on the network, we expect computation to become much quicker allowing for the rise of a truly global network.

III. Edge computing with end-devices

There is a growing body of work focusing on exploiting connectivity among end-devices, in particular mobile devices (mobile cloud computing), in close proximity to process tasks cooperatively in local area computation groups [24]. The end devices in a given area communicate with each other to find resources and deliver requests. Hence, the end-user stratum and the edge stratum are merged. In the literature, collaboration is a central feature: [25] propose a vision where mobile devices form "mobile clouds", or mClouds to accomplish tasks locally; [26] propose "Transient Clouds" as a collaborative computing platform, where nearby devices form an ad-hoc network and provide various capabilities as cloud services; [27] propose a resource sharing mechanism to utilize capable mobile devices through opportunistic contacts between them. Emphasizing resource aspects of mobile cloud computing, [28] focus on virtual machine technology (VM) to harness the full power of local hardware at the edges of the Internet, while [29] proposing an adaptive method of resource discovery and address service provisioning in opportunistic computing environments for managing higher load requests without causing instability [30]. Sharing some similarities with the OMNIBUS project, [31] propose an architecture called Vehicular Fog Computing (VFC) for vehicular applications. While this preliminary work also refers to vehicles (both moving and parked) as an infrastructure for communication and computation, it does so to service vehicles alone and not servicing all other connected devices and applications. In all proposals, regarding edge computing that merge the end-user stratum and the edge stratum, devices share their resources among each other in a limited area.

IV. OMNIBUS Architecture and Implementation

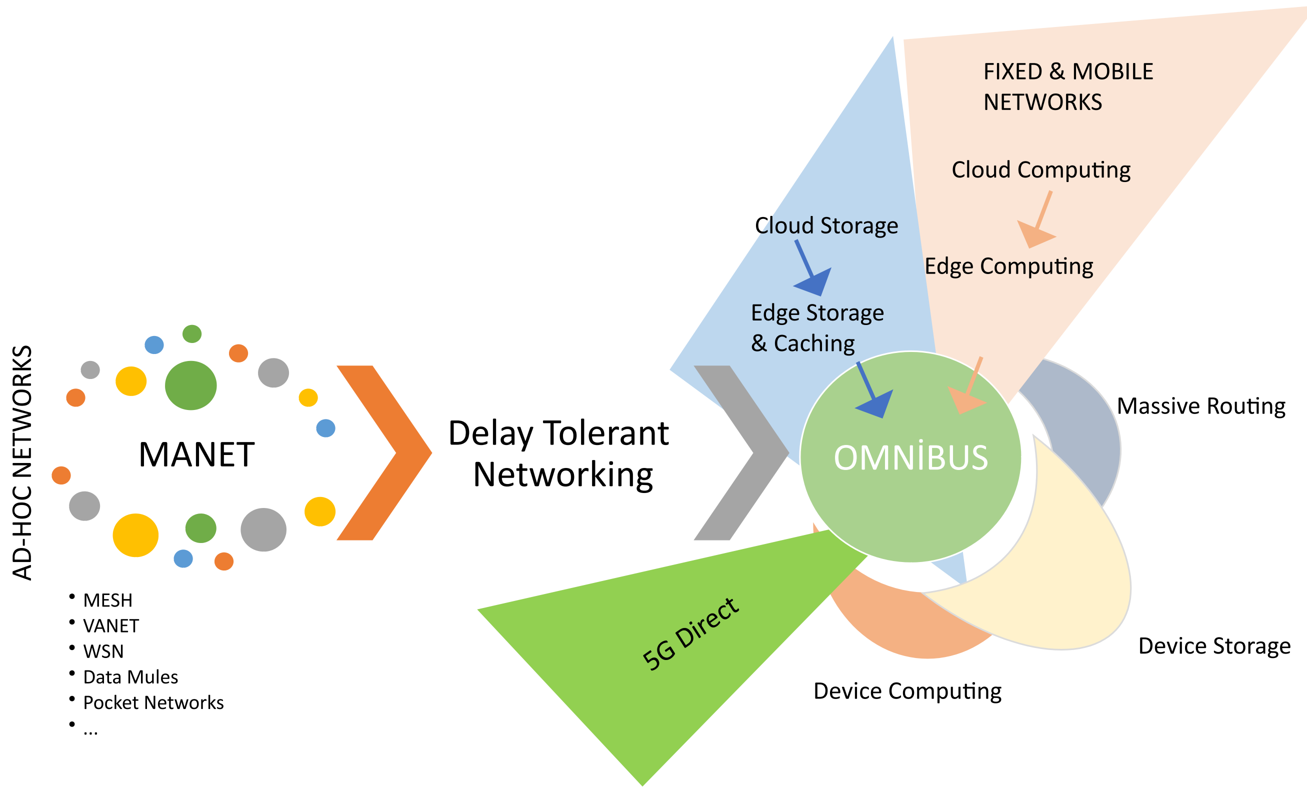
The OMNIBUS proposal expands the idea of end user stratum and the edge stratum to the next level. By introducing a predictive platform for mobility patterns and for the distribution of storage and computation capacity among cars, it paves the way for an efficient and highly scalable architecture for device-level edge computing.

Distributed machine learning and model parallelism. In the case of large-scale Machine Learning (ML), which means access to large data resources, our goal is to speed it up by reducing training time, by means of parallel or distributed computing. Data parallelism and model parallelism are also methods of speeding. Data parallelism partitions the data. In model parallelism, our approach partitions the ML model itself to distribute the workload to multiple computational workers. In our architecture, it is necessary to understand ways to partition the ML model according to heterogeneity and mobility of cars, as well as ,with an eye to ensure interoperability on the level of different service providers. Given the high number of machine learning models, with each model having its own characteristics and representations, there is no principle way to implement model parallelism. In distributed machine learning, the synchronization overhead increases as the systems scales.

Our approach also leverages automatic machine learning software methods to optimize the hyper-parameters of selected algorithms. Furthermore, it utilizes Hadoop frameworks, including Hadoop Distributed File System (HDFS), Spark, and Cassandra for faster and energy efficient computation. The Hadoop framework employs simple programming models that allow for the distributed processing of large data sets across clusters of computers. Spark is a compute engine for Hadoop data that supports an entire range of applications, e.g. machine learning, stream processing, etc. Cassandra is a high scalable database with no single point of failure, which makes it ideal for mission critical data.

Next generation distributed ledger technology. For stor-

Fig. 4. A Distributed Machine Learning Example



ing data and enabling fast computation in the network, it is very important to study directed acyclic graphs (DAG) based ledger technology. DAG may be the primary data structure for us to create a peer-to-peer network protocol. This will let us advance, in distributed machine learning methods, to add cognitive capabilities, as well as, consensus mechanisms.

DAG is largely more suitable for our project, due to its scalability potential and lesser processing power requirements compared to Bitcoin-like blockchain ledger technologies [32, 33]. In the blockchain system, the block size and the time required to generate a new block puts limitations on throughput and transaction times. In contrast to blockchain technology, DAG transactions are not grouped into blocks. Each new transaction confirms at least one previous transaction and transactions are represented as “units.” Hence, selection of a branch selection and detection of double-transaction is decoupled from transaction verification, which allows nodes to verify transactions in parallel. As a result, DAG has the potential to achieve unlimited scalability.

However, as DAG based projects emerge for high-frequency transaction scenarios, problems may arise in low frequency transaction [32]. When an old transaction is not able to receive a sufficient number of new transactions to verify, the old transaction may not be confirmed in time or not be confirmed at all. To ensure a continuous system, our approach optimizes high frequency and low frequency transactions by harmonizing DAG and Blockchain concepts as required.

Mobility models. Mobility data contains the approximate whereabouts of individuals and is used to explore the movement patterns of individuals across space and time. The vehicular mobility maps have been addressed in the literature [34, 35, 36]. However, they are not comprehensive enough. Moreover, mobility data is among the most sensitive data currently being collected. While the discussion on individual privacy with respect to mobility data is on the rise, research in this area is still limited [37, 38, 39, 40]. The OMNIBUS project proposes to design a targeted mobility model, addressing specific tasks that do not compromise an individual’s privacy. In doing this, leveraging automatic machine learning software methods and distribute ledger technologies is very important.

V. Methodology

(a) Aggregated Mobility Handling (AMH): AHM aims to accurately depict vehicular behavior and focuses on the following principles: (i) Charting out mobility patterns of moving cars, in order to optimize the computing and storage distribution among them. Mobility patterns will be learned in mixed autonomy with each car sharing the mobility patterns and movements of the other cars. (ii) Aggregation, which will take place over a combination of DAG and Blockchain based distributed ledger technologies, depending on different

frequency scenarios. (iii) Leveraging our model to solve the massive routing problem, to bring Internet data to unconnected regions.

(i)Solving the Mobility Handling Problem: Self-driving cars, ride sharing, and similar exercises in mobility as a service (MaaS) are turning transportation into mixed autonomy systems, integrating AI/ML technology. By reducing randomness, mixed autonomy systems, including autonomous and non-autonomous vehicles, make it possible to accurately depict vehicular behavior (the mobility handling problem) [41, 42]. In this relation, mobility pattern challenges and requirements of mixed autonomy systems are studied; more specifically, a convex optimization method predicting flow is used to represent coordination of automated vehicles, which relies on accurate traffic flow sensing [43, 44, 4]. MaaS applications enable user induced non-autonomy systems to turn a generally assumed to be intractable problem into a mixed-autonomy problem. In the context of a larger dynamical system, this dictates the progression of the integration or the use of automation [43].

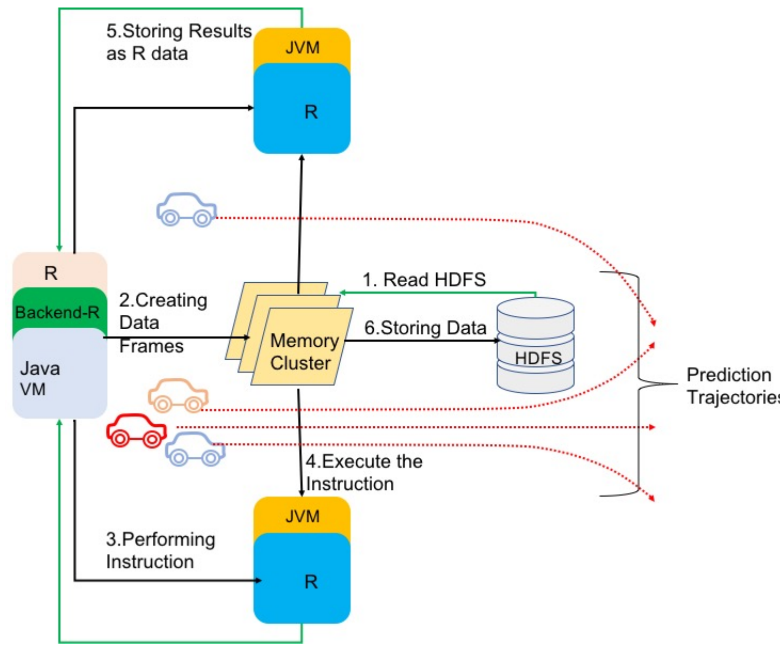
Our approach is to first generalize the mobility handling problem, using generic reinforcement learning techniques for improved dimension reduction. It applies machine learning and optimization methods to mixed autonomy systems, to address the automation problems of integration into existing systems. It explores empirical and theoretical justifications of edge/caching systems and their optimization methods as a design paradigm. Through principled learning and optimization methods, even a small number of vehicles can be harnessed for significant impact on the Internet.

At this point, real-time independent decision making for the random behavior of car passengers & drivers is a crucial factor. For this reason, creating a sequential decision-making tool/program, to model the learning and decision-making processes of car passengers and/or drivers, would be the first to be acknowledged. As commuters make repeated decisions, they learn over time to optimize their route choices. This can be efficiently modeled by a sequential process, where they optimize a payoff function at each step, linked to the results they experience.

Our model will also leverage the existing literature on traffic systems that can often be modeled using complex (nonlinear and coupled) dynamical systems. In addressing complex traffic control problems, it should be developed a decentralized, learning-based approach involving interactions of humans, automated cars, and sensing infrastructure, using deep reinforcement learning. The resulting control laws and emergent behaviors of cars will potentially provide insight for the behavior of each car. These insights will be replicated, shared, and synchronized among cars, over a distributed ledger technology, through peer-to-peer ad-hoc networking to understand the potential for automation of flow. We have already carried out a simulation for a two lane road to demonstrate the possibility of computation and storage period [45].

Our novel computational framework that integrates open-source deep learning and simulation tools can support the development of edge computing in vehicles, in the context of complex nonlinear dynamics of transportation. Learned policies, resulting from effectively leveraging the structure of human driving behavior, surpass the performance of state-of-the-art predictors designed for various mobile applications, such as Google Now. The framework will initially focus on highway traffic, and later will include arterial traffic, transit, as well as, other modes of transportation / commuting (biking, MaaS, carpooling, etc.)

Fig. 5. A demonstration of machine learning software programming with Hadoop Distributed File System distributed over cars. JVM is Java Virtual Machine.

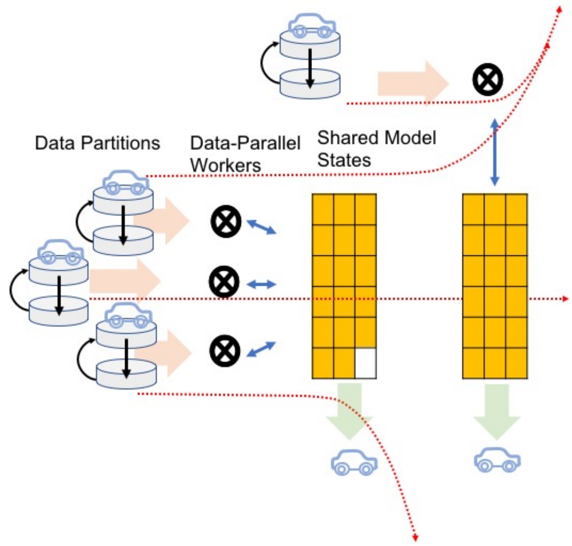


(ii)Distributed Ledger as a Database: DAG is going to be used in distributed ledger technologies for storing data to enable fast and scalable computation in the network. DAG may be the primary data structure for the OMNİBUS approach to create a peer-to-peer network protocol. However, as DAG based projects emerge for high-frequency traffic scenarios, problems may arise in low frequency. To ensure a continuous hybrid system, utilizing sequential Blockchain verification to parallel DAG verification mechanism is necessary to accommodate increasing and unreliable penetration.

(iii) Solving the Massive Routing Problem: Mobility patterns is crucially important in the context of providing network access to areas without Internet, by adding a spatial component to the temporal sequential process, which may be termed as "Cartesian" machine learning. In doing so, understanding the "next move" to be utilized as the "next hop" in routing purposes is essential. The techniques we develop in this regard leverage known models, such as the replicator dynamics, mirror descent, stochastic gradient descent, and the hedge algorithm. Overall, it is necessary to achieve convergence of all these processes towards a set of equilibria based on assumptions made on the learning process used by humans in decision-making, taking into consideration constraints imposed by transportation.

(b) Decentralizing computing and storage Anticipating the demand for each edge car and deploying adequate car

Fig. 6. A Distributed Machine Learning Example



resources are very important to sufficiently meet locational demands. For instance, when a single car moves out of the local area, its storage and computing resources will need to be distributed across the cars that remain in that area and new cars that enter the area.Thus, developing predictive algorithms is very necessary to optimally distribute computing and storage resources among cars, taking into account challenges related to redundancy, security, heterogeneity of devices, and federation (that interoperability is ensured on the level of different service providers). In developing these algorithms, creating and employing a global mobility map is a key element. Leveraging and combining existing mesh networking systems for car-to-car car-to-device communication is also necessary. In addition, studying how to distribute computing and storage across the entire system, i.e. whether data should remain local (shared among cars) or be sent to the cloud, would be equally important.

Another important task would be building parallel systems that harnessing thousands of simple and efficient computing and storage resources would be a practical approach to sustain growth without scaling technology. To this end, our architecture parallelizes algorithms. Tasks need to be implemented speculatively and in an out of order manner. Moreover, thousands of tasks need to be speculated efficiently prior to the earliest active task in order to reveal sufficient parallelism. To develop parallel algorithms and uncover an abundant parallelism in large-scale applications, a new techniques need to develop to exploit locality and nested parallelism. In order to generate parallel algorithms in cars, it should be focused on the following:

(i) Ensuring consensus among multiple cars working towards a common goal, for instance, when all cars involved are solving one optimization problem together, yet with different partitions of the dataset. (ii) Redistribution in the emergency of one of the cars being disabled and leaving the cluster. The issue is to restore the system without restarting it. (iii) Communication.Computation requires a lot of input/output (I/O) (e.g. disk read and write) and data processing procedures. OMNIBUS approach distributed storage systems to enable faster I/O and non-blocking data processing procedures for different types of environments (e.g. single node local disk, distributed file systems, etc.) Managing resources. The issue is one of managing resources within a given cluster of cars to meet all demands while maximizing capacity. (iv) Designing a programming model to improve efficiency. A new programming model is employed to achieve distributed computing and storage algorithms, in the same way as non-distributed ones, which requires less coding and improves efficiency. Studying programming in a single-node fashion, while automatically amplifying the program with distributed computing techniques, is also necessary. Applying model parallelism partitioning, to the ML model itself, to distribute the workload to multiple computational cars is also very important, as well as developing a unique data analytics engine, specifically, targeting the car to car and car to connected device, for big data processing.

VI. Challenges

(a) Decentralizing computing and storage: The demand for each edge car needs to be anticipated so that adequate car resources are deployed to meet locational demands. For instance, when a single car moves out of the local area, its storage and computing resources will need to be distributed across other cars that remain in that area and new cars that enter the area. Our architecture leverages an excessive mobility map in developing predictive algorithms to optimally distribute computing and storage resources among cars. In doing this, it is necessary to take into account challenges related to redundancy, security, heterogeneity, and federation that interoperability are ensured on the level of different service providers and mobility handling. OMNIBUS model leverages and combine existing MANET (Mobile Ad-hoc Network), VANET (Vehicular Ad-hoc Network) and DTN (Delay Tolerant Networking) technologies for car-to-car and car-to-device communication. Moreover, this model also looks at how to distribute computing and storage across the entire system, i.e. whether data should remain local (shared among cars) or be sent to the cloud.

(b) Aggregated Mobility Handling (accurately depicting vehicular behavior): At present, there is no large-scale mobility map; available models are not adaptable, and they do not adequately address privacy concerns. In our architecture, developing a mobility prediction model is critical for optimizing the allocation of computing and storage resource sharing among them. These mobility patterns enable us to provide for offloading decisions, as well as, to control energy consumption and bytes of data transfer [46, 47]. Our approach will use databases provided by mobile operators, smart transportation systems, etc. to build our mobility model. Mobility patterns will be learned and each car shares mobility patterns and movements of other cars via mesh networking technologies. OMNIBUS model uses a combination of DAG based and Blockchain based distributed ledger technologies depending on different frequency scenarios for aggregation. Our problem is complex since it focuses on continuously

moving cars exchanging data with each other, in order to keep the system alive in any given location. Proposed solutions to communication regarding moving vehicles are so far limited to highly ordered environments. In contrast, OMNIBUS approach seek to develop communication protocols for cars in a highly chaotic environment. To do this, OMNIBUS model leverages MANET, VANET, and DTN technologies.

(c) Heterogeneity issues: Heterogeneity of resources, in terms of computational and storage capabilities, as well as, their ad-hoc availability, is necessary to optimize. Heterogeneity is important in deciding which application component needs to be deployed and where it should it deployed [20]. This involves developing algorithms to address heterogeneity taking into account the limitations of specific nodes. For instance, in a content delivery use case, storage limitations of the caches are incorporated into the caching algorithm. Furthermore, while node degrees can be optimized, each cars CPU will need to compute multiple items at the same time. Ensuring that CPUs are not overwhelmed will be a key consideration in developing our algorithms.

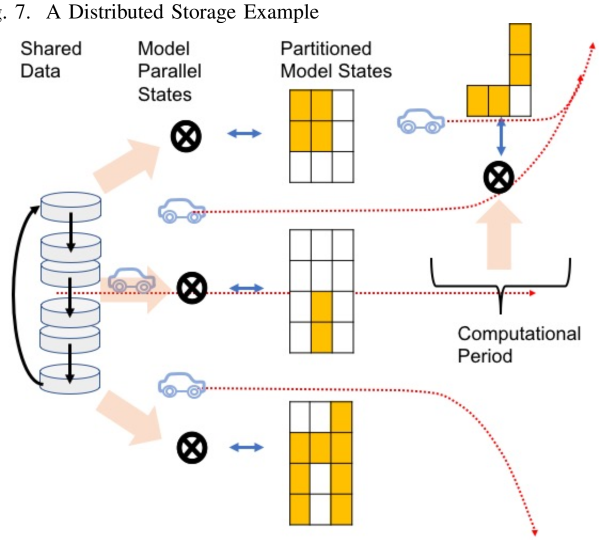
(d) Federation issues: In our architecture, cars are geographically distributed on a very wide scale and could be assigned to different service providers. Moreover, the cloud can be operated by a different provider. Our architecture will be designed in a way that interoperability is ensured on the level of federation of different service providers. This means developing a consensus protocol to understand capabilities of a variety of cars using different providers.

(e) Handling mobility of end-users: In the case that end-users physically move, the system should be able to continuously provide them with the same quality of experience, without interrupting the service. Furthermore, in the scenario that several end-users are watching the same video, the algorithm may need to allow for the mobility engine to copy the video to be pushed to the destination point. Similarly, as a car moves in our system, resource displacement takes place with implications on resource management algorithms. In addressing this challenge, studying byzantine fault tolerance methods, for scenarios where a car's data center may fail or move, is important and there is imperfect information on whether a component has failed or moved. OMNIBUS approach applies model parallelism partitioning the ML model itself to distribute the workload to multiple computational cars. In this architecture, understanding ways to partition the ML model according to heterogeneity, federation, and mobility constantly be investigated.

VII. Impact

The OMNIBUS project will have a far-reaching impact in three areas summarized below: **(i) 5G and 6G Ultra-Reliable Low Latency Communication (URLLC):** Ultra low-latency, the project's key objective, is to enable a range of new applications (Smart driving, Smart Grids, Augmented Reality, and IoT in general), which depend on ultra-reliable and ultra-low-latency connectivity. The OMNIBUS project is driven by the need to remove present and future bottlenecks in communication networks and to prepare the groundwork for future 5G and 6G heterogenous networks [48, 49, 50, 51, 52, 53]. The project responds to the market need for a comprehensive edge network platform for faster and more reliable data processing. Attempts to move computing closer to the network (Cloudlets, Fog computing, MEC) are not scalable. In contrast, our architecture has the potential to scale almost infinitely and increases the speed of networks while it grows. Our ambitions go further and our research paves the way for employing all connected devices, including persons with smart phones and all IoT applications, as computing and storage centers. The decentralized network architecture, we propose, opens up new possibilities for network slicing, hence, lower latency, more storage capacity, more network resilience and security, and less energy waste. By breaking down and distributing computing and storage resources for intermittent networking, our approach leads the way for a scalable collaborative communication network.

Fig. 7. A Distributed Storage Example



(ii) Decentralized Internet: Our framework architecture can be used for high latency, delay tolerant Internet access for more than 3.9 billion of the world's population, who remain offline today. A decentralized storage and computational framework, like the one we propose, is more reliable than current digital infrastructures, which are vulnerable to disaster situations, where a single point of failure in the infrastructure can bring down the entire communication network.The OMNIBUS approach leverages our mobility model to solve the massive routing problems and predictive algorithms we develop to optimally distribute computing and storage among cars, to bring Internet data to unconnected regions. In this regard, the OMNIBUS project is expected to open new directions in research on ad hoc technologies and DTN-based data mules. As opposed to URLLC, this can be named as UCHLC: Ultra Coverage High Latency Communication.

(iii) Smart transportation: Our project will have considerable impact on smart transportation systems, including traffic systems and edge computing in vehicles. It has the potential to redirect research on traffic systems towards a decentralized, learning-based study of complex traffic control problems, involving interactions of humans, automated vehicles, and

sensing infrastructure. The resulting control laws and emergent behaviors of cars will potentially provide insight for the behavior of each car. These insights will be replicated, shared, and synchronized among cars, over a distributed ledger technology through peer-to-peer ad-hoc networking, to understand the potential for automation of flow.

Furthermore, our research can be employed by the research community as a new computational framework that integrates open-source deep learning and simulation tools, to support the development of edge computing in vehicles, in the context of complex nonlinear dynamics of transportation. Learned policies, resulting from effectively leveraging the structure of human driving behavior will support and further develop state-of-the-art predictors designed for various mobile applications, such as Google Now; it will also make existing map databases more accurate and more interactive.

VIII. Summary

A breakthrough development is imminently needed, in order to support the demands of the data heavy network edge. Even though, there are various proposed solutions regarding Edge computing, most of them are substantially limited and not easily scalable. At this point, the OMNIBUS project offers a breakthrough technology, by bringing together a full spectrum of science and engineering used for different innovations and has the potential to upend the ecosystem for future network efforts. This solution, especially, paves the path for more efficient and highly scalable device-level edge computing architectures. It, specifically, develops serious key objectives to enable a range of new applications (Smart driving, Smart Grids, Augmented Reality, and IoT in general), which depend on ultra-reliable and ultra-low-latency connectivity. OMNIBUS project has the potential to redirect research on traffic systems towards a decentralized, learning-based study of complex traffic control problems. Furthermore, it can be employed by the research community as a new computational framework that integrates open-source deep learning and simulation tools, to support the development of edge computing in vehicles, in the context of complex nonlinear dynamics of transportation. It can support and further develop state-of-the-art predictors designed for various mobile applications, such as Google Now; it will also make existing map databases more accurate and more interactive. The OMNIBUS solution will be the most important and influential building block for future network efforts.

Acknowledgment

Bibliography

[1] J. Manyika, M. Chui, P. Bisson, J. Woetzel, R. Dobbs, J. Bughin, and D. Aharon, "The internet of things: Mapping the value beyond the hype, mckinsey global institute, june 2015," 2016.

[2] D. Evans, "The internet of things: How the next evolution of the internet is changing everything," *CISCO white paper*, vol. 1, no. 2011, pp. 1–11, 2011.

[3] S. Y. Cheung, S. C. Ergen, and P. Varaiya, "Traffic surveillance with wireless magnetic sensors," in *Proceedings of the 12th ITS world congress*, vol. 1917, 2005, p. 173181.

[4] S. Y. Cheung, S. Coleri, B. Dundar, S. Ganesh, C. woo Tan, and P. Varaiya, "Traffic measurement and vehicle classification with a single magnetic sensor. transportation research," 2005.

[5] N. Akhtar, S. C. Ergen, and O. Ozkasap, "Vehicle mobility and communication channel models for realistic and efficient highway vanet simulation," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 1, pp. 248–262, Jan 2015.

[6] C. K. Dominicini, G. L. Vassoler, L. F. Meneses, R. S. Villaca, M. R. N. Ribeiro, and M. Martinello, "Virtphy: Fully programmable nfv orchestration architecture for edge data centers," *IEEE Transactions on Network and Service Management*, vol. 14, no. 4, pp. 817–830, Dec 2017.

[7] T. Taleb, K. Samdanis, B. Mada, H. Flinck, S. Dutta, and D. Sabella, "On multi-access edge computing: A survey of the emerging 5g network edge cloud architecture and orchestration," *IEEE Communications Surveys Tutorials*, vol. 19, no. 3, pp. 1657–1681, thirdquarter 2017.

[8] M. Marjanović, A. Antonić, and I. P. Žarko, "Edge computing architecture for mobile crowdsensing," *IEEE Access*, vol. 6, pp. 10 662–10 674, 2018.

[9] P. K. Sharma, S. Rathore, Y. Jeong, and J. H. Park, "Softedgenet: Sdn based energy-efficient distributed network architecture for edge computing," *IEEE Communications Magazine*, vol. 56, no. 12, pp. 104–111, December 2018.

[10] H. El-Sayed, S. Sankar, M. Prasad, D. Puthal, A. Gupta, M. Mohanty, and C. Lin, "Edge of things: The big picture on the integration of edge, iot and the cloud in a distributed computing environment," *IEEE Access*, vol. 6, pp. 1706–1717, 2018.

[11] M. Chiang and T. Zhang, "Fog and iot: An overview of research opportunities," *IEEE Internet of Things Journal*, vol. 3, no. 6, pp. 854–864, Dec 2016.

[12] J. Pan and J. McElhannon, "Future edge cloud and edge computing for internet of things applications," *IEEE Internet of Things Journal*, vol. 5, no. 1, pp. 439–449, Feb 2018.

[13] P. Corcoran and S. K. Datta, "Mobile-edge computing and the internet of things for consumers: Extending cloud computing and services to the edge of the network," *IEEE Consumer Electronics Magazine*, vol. 5, no. 4, pp. 73–74, Oct 2016.

[14] L. L. K. P. R. S. A. S. M. T. D. V. R. W. Carrie MacGillivray, Vernon Turner and R. Yesner, "Idc futurescape: Worldwide internet of things 2017 predictions," *IDC*, vol. 2017, pp. 1–17, 2017.

[15] M. Satyanarayanan *et al.*, "Pervasive computing: Vision and challenges," *IEEE Personal communications*, vol. 8, no. 4, pp. 10–17, 2001.

[16] R. Balan, J. Flinn, M. Satyanarayanan, S. Sinnamohideen, and H.-I. Yang, "The case for cyber foraging," in *Proceedings of the 10th workshop on ACM SIGOPS*

European workshop. ACM, 2002, pp. 87–92.

[17] M. Satyanarayanan, P. Bahl, R. Caceres, and N. Davies, "The case for vm-based cloudlets in mobile computing," *IEEE pervasive Computing*, no. 4, pp. 14–23, 2009.

[18] Y. C. Hu, M. Patel, D. Sabella, N. Sprecher, and V. Young, "Mobile edge computing—a key technology towards 5g," *ETSI white paper*, vol. 11, no. 11, pp. 1–16, 2015.

[19] Cisco, "Fog computing and the internet of things: Extend the cloud to where the things are," *Cisco White Paper*, 2015.

[20] C. Mouradian, D. Naboulsi, S. Yangui, R. H. Glitho, M. J. Morrow, and P. A. Polakos, "A comprehensive survey on fog computing: State-of-the-art and research challenges," *IEEE Communications Surveys Tutorials*, vol. 20, no. 1, pp. 416–464, Firstquarter 2018.

[21] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Communications Surveys Tutorials*, vol. 19, no. 4, pp. 2322–2358, Fourthquarter 2017.

[22] F. Bonomi, R. Milito, J. Zhu, and S. Addepalli, "Fog computing and its role in the internet of things," in *Proceedings of the first edition of the MCC workshop on Mobile cloud computing*. ACM, 2012, pp. 13–16.

[23] Cisco, "Cisco fog computing solutions: Unleash the power of the internet of things," *Cisco USA*, 2015.

[24] R. K. Lomotey and R. Deters, "Architectural designs from mobile cloud computing to ubiquitous cloud computing-survey," in *2014 IEEE World Congress on Services*. IEEE, 2014, pp. 418–425.

[25] E. Miluzzo, R. Cáceres, and Y.-F. Chen, "Vision: mclouds-computing on clouds of mobile devices," in *Proceedings of the third ACM workshop on Mobile cloud computing and services*. ACM, 2012, pp. 9–14.

[26] T. Penner, A. Johnson, B. Van Slyke, M. Guirguis, and Q. Gu, "Transient clouds: Assignment and collaborative execution of tasks on mobile devices," in *2014 IEEE Global Communications Conference*, Dec 2014, pp. 2801–2806.

[27] W. Liu, R. Shinkuma, and T. Takahashi, "Opportunistic resource sharing in mobile cloud computing: The single-copy case," in *The 16th Asia-Pacific Network Operations and Management Symposium*, Sep. 2014, pp. 1–6.

[28] M. Satyanarayanan, S. Smaldone, B. Gilbert, J. Harkes, and L. Iftode, "Bringing the cloud down to earth: Transient pcs everywhere," in *Mobile Computing, Applications, and Services*, M. Gris and G. Yang, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 315–322.

[29] W. Liu, T. Nishio, R. Shinkuma, and T. Takahashi, "Adaptive resource discovery in mobile cloud computing," *Computer Communications*, vol. 50, pp. 119 – 129, 2014, green Networking.

[30] D. Mascitti, M. Conti, A. Passarella, and L. Ricci, "Service provisioning through opportunistic computing in mobile clouds," *Procedia Computer Science*, vol. 40, pp. 143 – 150, 2014, fourth International Conference on Selected Topics in Mobile Wireless Networking (MoWNet'2014).

[31] X. Hou, Y. Li, M. Chen, D. Wu, D. Jin, and S. Chen, "Vehicular fog computing: A viewpoint of vehicles as the infrastructures," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 3860–3873, June 2016.

[32] F. M. Benčić and I. Podnar Žarko, "Distributed ledger technology: Blockchain compared to directed acyclic graph," in *2018 IEEE 38th International Conference on Distributed Computing Systems (ICDCS)*, July 2018, pp. 1569–1570.

[33] K. Yeow, A. Gani, R. W. Ahmad, J. J. P. C. Rodrigues, and K. Ko, "Decentralized consensus for edge-centric internet of things: A review, taxonomy, and research issues," *IEEE Access*, vol. 6, pp. 1513–1524, 2018.

[34] D. Naboulsi and M. Fiore, "On the instantaneous topology of a large-scale urban vehicular network: The cologne case," in *Proceedings of the Fourteenth ACM International Symposium on Mobile Ad Hoc Networking and Computing*, ser. MobiHoc '13. New York, NY, USA: ACM, 2013, pp. 167–176.

[35] P. E. Luo, H. Y. Huang, and M. L. Li, "Characteristics of trace data for a large scale ad hoc network — shanghai urban vehicular network," in *2007 IET Conference on Wireless, Mobile and Sensor Networks (CCWMSN07)*, Dec 2007, pp. 742–745.

[36] F. K. Karnadi, Z. H. Mo, and K. Lan, "Rapid generation of realistic mobility models for vanet," in *2007 IEEE Wireless Communications and Networking Conference*, March 2007, pp. 2506–2511.

[37] Z. Tu, F. Xu, Y. Li, P. Zhang, and D. Jin, "A new privacy breach: User trajectory recovery from aggregated mobility data," *IEEE/ACM Transactions on Networking*, vol. 26, no. 3, pp. 1446–1459, June 2018.

[38] Z. Lu, G. Qu, and Z. Liu, "A survey on recent advances in vehicular network security, trust, and privacy," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 2, pp. 760–776, Feb 2019.

[39] F. A. Ghaleb, M. A. Razzaque, and I. F. Isnin, "Security and privacy enhancement in vanets using mobility pattern," in *2013 Fifth International Conference on Ubiquitous and Future Networks (ICUFN)*, July 2013, pp. 184–189.

[40] Y.-A. de Montjoye, C. A. Hidalgo, M. Verleysen, and V. D. Blondel, "Unique in the crowd: The privacy bounds of human mobility," in *Scientific reports*, 2013.

[41] S. E. Shladover, G. Polatkan, R. Sengupta, J. VanderWerf, M. Ergen, and B. Bougler, "Dependence of cooperative vehicle system performance on market penetration," *Transportation Research Record*, vol. 2000, no. 1, pp. 121–127, 2007.

[42] I. Shayea, M. Ismail, R. Nordin, H. Mohamad, T. A. Rahman, , and N. F. Abdullah, "Novel handover optimization with a coordinated contiguous carrier aggregation deployment scenario in lte-advanced systems," vol. 2016, no. 1, pp. 1–20, 2016.

[43] C. Wu, "Learning and optimization for mixed autonomy systems - a mobility context," Ph.D. dissertation, EECS Department, University of

California, Berkeley, Sep 2018. [Online]. Available: http://www2.eecs.berkeley.edu/Pubs/TechRpts/2018/EECS-2018-132.html

[44] Y. Sadi and S. C. Ergen, "Minimum length scheduling with packet traffic demands in wireless ad hoc networks," *IEEE Transactions on Wireless Communications*, vol. 13, no. 7, pp. 3738–3751, July 2014.

[45] M. Ergen, "Critical penetration for vehicular networks," *IEEE Communications Letters*, vol. 14, no. 5, pp. 414–416, May 2010.

[46] P. Park, S. Coleri Ergen, C. Fischione, C. Lu, and K. H. Johansson, "Wireless network design for control systems: A survey," *IEEE Communications Surveys Tutorials*, vol. 20, no. 2, pp. 978–1013, Secondquarter 2018.

[47] Y. Sadi, S. C. Ergen, and P. Park, "Minimum energy data transmission for wireless networked control systems," *IEEE Transactions on Wireless Communications*, vol. 13, no. 4, pp. 2163–2175, April 2014.

[48] C. Backfrieder, G. Ostermayer, and C. F. Mecklenbräuker, "Increased traffic flow through node-based bottleneck prediction and v2x communication," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 2, pp. 349–363, Feb 2017.

[49] I. Shayea, M. Hadri Azmi, T. Abd. Rahman, M. Ergen, C. Tien Han, and A. Arsad, "Spectrum gap analysis with practical solutions for future mobile data traffic growth in malaysia," *IEEE Access*, vol. 7, pp. 24 910–24 933, 2019.

[50] G. T. F. d. A. Razvan Andrei Stoica, "6g: the wireless communications network for collaborative and ai applications," in *arXiv*, vol. 2019, 2019, pp. 1–2.

[51] A. P. Singh, S. Nigam, and N. K. Gupta, "A study of next generation wireless network 6g," *Int. J. of Innovative Research in Computer and Communication Engineering*, vol. 4, no. 1, pp. 871–874, 2007.

[52] A. Gawas, "An overview on evolution of mobile wireless communication networks: 1g-6g," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 3, no. 5, pp. 3130–3133, 2015.

[53] Y. Xing and T. S. Rappaport, "Propagation measurement system and approach at 140 ghz-moving to 6g and above 100 ghz," in *2018 IEEE Global Communications Conference (GLOBECOM)*. IEEE, 2018, pp. 1–6.